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A simulation-based design framework to iteratively analyze and shape urban landscapes using point cloud modeling

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ABSTRACT

The topic of this paper evolves on the discourse of digital modeling in landscape design. Current design methods stagger to address physical forms and dynamics present in the environment. This status quo limits possibilities to integrate scientific evidence when developing spatial and aesthetic configurations in urban landscapes. Remote sensing technology such as laser scanning measures physical forms to reproduce them as geo-specific digital 3D models, while dynamic simulation is widely used to predict how scenarios will perform under given conditions. However, there is still a need for a holistic design process that is capable of integrating both the measured physical forms and physical dynamics. This paper presents a novel framework using point cloud modeling to shape design scenarios that are iteratively evaluated for their performance.

The proposed framework is demonstrated through a case study in Singapore. New spatial configurations are tested for the site through an iterative and comparative analysis of the design performance. The case study exposes (1) a site-specific design approach by iteratively modeling a laser-scanned point cloud model, (2) a workflow to convert the geometric data from the point cloud models into voxels and meshes, (3) an integration of computational fluid dynamics (CFD) simulation during design development as per-point attributes, and (4) a comparison of the configurations to identify best performing scenarios.

This design framework can support city managers, planners, urban and landscape designers to better inform their decision-making process by relying on accurate scientific feedback. By guiding the design process with the consideration of the built environment as a complex adaptive system, it will be possible to improve how open spaces and ecosystem services perform in cities, and to design landscapes that can mitigate dynamic events such as urban heat islands.

1. Introduction

Current practice and theory in landscape design increasingly use digital methods to integrate dynamic conditions of the environment with scientific feedback to predict how designs will perform when they are implemented (Grêt-Regamey et al., 2014; Walliss, 2018). The notion of "digital twin" has emerged to describe the simulation of physical assets in time and at various frequencies for monitoring and planning cities (Batty, 2018). When included as a framework for design, such dynamic simulation can be employed to test and optimize prospective scenarios (Cheshmehzangi, 2016; Chung & Choo, 2011; Moonen, Defraeye, Dorer, Blocken, & Carmeliet, 2012). In this case, the combination of two main components is used to predict how design scenarios will perform in future and over time: (1) *digital models* to study the physical geometry of the design, and (2) *dynamic simulation* to investigate the time-varying behavior of dynamic systems that come in contact with the form (Girot & Urech, 2016; Oxman, 2008).

1.1. Digital models

In the past, digital three-dimensional (3D) city models served a relatively limited community of geospatial experts (Sinning-Meister, Gruen, & Dan, 1996). Nowadays, such models have become ubiquitous due to their various applications, including mapping, visualization, generation of digital and physical models, performance assessment, environmental monitoring, simulation, and more (Biljecki, Stoter,

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Ledoux, Zlatanova, & Çöltekin, 2015; Park & Guldmann, 2019; Richter, Kyprianidis, & Döllner, 2013; Schrotter & Hürzeler, 2020). Significant improvement in detail and precision was achieved with airborne and terrestrial laser scanning (ALS/TLS). This remote sensing technology, also referred to as LiDAR (light detection and ranging), produces spatial data suited to reconstruct 3D city models by using methods such as Digital Elevation Model (DEM) generation (Kraus & Pfeifer, 1998), boundary tracing (Heo et al., 2013), building extraction (Park & Guldmann, 2019), building and urban parameterization (Bonczak & Kontokosta, 2019; Gonzalez-Aguilera, Crespo-Matellan, Hernandez-Lopez, & Rodriguez-Gonzalvez, 2013), etc. However, when directly visualized in digital space, the coordinate points of LiDAR data form models that offer analytical capabilities. These point cloud *models* can be used for dynamic visualization (Nebiker, Bleisch, & Christen, 2010), spatial change detection (Richter et al., 2013), identification of morphologic accumulation (Urech, 2020), and evaluation of landscape characteristics (Sedláček, Klepárník, & Kopřivová, 2020).

1.2. Dynamic simulation

The geometry used in digital 3D models usually provides a static representation of urban and natural environments (e.g. buildings, vegetation, streets, open spaces, water features, topography, etc.) (Jochem, Höfle, Wichmann, Rutzinger, & Zipf, 2012), offering a limited application for analytical purposes (Bonczak & Kontokosta, 2019). However, prospective scenarios must take into account dynamic interactions that occur on varying time scales and degrees depending on location, materials and processes at play (Pickett et al., 2017). Dynamic systems follow patterns that perform inseparably from the virtual and physical environment (M'Closkey & VanDerSys, 2017). Such systems call for designers to predict how designs will perform under changing conditions such as the action of water, weather patterns, vegetation growth, and anthropogenic activities (McCown & Zawarus, 2016). Designing with a 'systems-thinking approach' increases the design choice and enables a continuous information exchange suited to the management of contemporary landscapes (Picon, 2013). The dynamic correspondence between 3D models and the real landscape enables algorithms to act as design tools within the digital environment (Cantrell & Mekies, 2018). As such, dynamic simulation supports the decision-making process of prospective scenarios using dynamic spatial models such as agent-based modeling (Gebetsroither-Geringer, 2014; Macal, 2016) or cellular automata (Fricker, Kotnik, & Piskorec, 2019; Santé, García, Miranda, & Crecente, 2010; Tong & Feng, 2019). Computer programs emulating dynamic systems influence how scientific knowledge is included in designing alternative scenarios (Ervin, 2014). In urban physics, simulation has been implemented for climate study in urban transformations (Moonen et al., 2012), wind simulation with photogrammetric reconstruction (Sun et al., 2021), microclimate analysis (Koc, Osmond, Peters, & Irger, 2017; Kugler, Tóth, Szalay, Szagri, & Barsi, 2019), radiative transfer modeling (Calders et al., 2018), shadow effect modeling (Bohn Reckziegel, Rafael, Sheppard, Kahle, & Morhart, 2021), and transpiration simulation (Bournez et al., 2019). Such simulations represent a major asset in planning future cities with climate scenarios (Schrotter & Hürzeler, 2020).

1.3. Research aim

Digital methods, as cited above, influence landscape design thinking and gradually replace diagrams and mapping techniques to develop and test projects (Herrington, 2016, 251–65; McCown & Zawarus, 2016). Resulting digital workflows pervade both design practice and research (Cantrell & Yates, 2012; Fricker et al., 2019; Walliss, Hong, Rahmann, & Sieweke, 2014). However, 3D models used in these workflows are typically geometric reconstructions that only offer indicative features of the landscape and differ considerably from the actual micro- and meso-scale environment (Nebiker et al., 2010). Moreover, the complex, dynamic and temporally heterogeneous interactions of urban and natural systems are not fully incorporated into modeling and simulation workflows (Bartesaghi-Koc, Osmond, & Peters, 2020; Bishop, Pettit, Sheth, & Sharma, 2013; Cadenasso, Pickett, McGrath, & Marshall, 2013; Pickett et al., 2017). From a city modeling perspective, urban vegetation, compared to buildings, has received less attention or has been even omitted. Therefore, current digital models offer limited information about trees (i.e. height, crown size, foliage distribution, etc.) hindering a more accurate and comprehensive microclimate analysis (Xu, Wang, Shen, & Zlatanova, 2021). Thus, the combination of the two components of digital models and dynamic simulation call for further exploration.

To address these shortcomings, the key aim of this study is to develop a holistic design framework—with the consideration of the built environment as a complex adaptive system—which iterates (1) 3D modeling using detailed geospatial data measured by laser-scanning with (2) computational fluid dynamics (CFD) simulation. This integration introduces a design process to access complex and specific forms and aesthetics of urban landscapes—e.g. complex vegetation geometries and patterns—and accurately transform them according to their best potential performance. In this context, the main objectives of this paper are twofold. First, to present a novel design framework based on point cloud modeling that harnesses the physical form of a site and steers the design process using comprehensive feedback relying on scientific evidence. Second, to demonstrate and discuss the applicability of this approach using Singapore as case study.

2. A holistic landscape design framework based on iterative point cloud modeling

The underlying idea of the proposed framework follows a traditional design thinking process in which initial surveys lead to proposals that are prototyped and tested (Norman, 2013, 217–30), allowing for inductive and deductive logics (Turner, 1996, 148–53). The framework consists of an iterative modeling workflow that gradually and specifically alters visual and spatial configurations of the landscape. The configurations are documented by point cloud models that contain contextual and morphologic information and are evaluated for their performance.

2.1. Point cloud modeling

The applications with LiDAR data cited in the introduction are analytical and intrinsic to the surveyed locations. In contrast, point cloud *modeling* is a process of selectively manipulating the geometry of 3D point cloud models. The manipulation is deduced from existing spatio-visual configurations and induces creative and functional intentions to develop new design scenarios (Urech, Dissegna, Girot, & Grêt-Regamey, 2020). This manipulation involves digital processing techniques such as classification and segmentation (e.g., Jochem et al., 2012; Nguyen & Le, 2013, 3; Yan, Shaker, & El-Ashmawy, 2015), allowing to cut, filter and disassemble the geometry (Fig. 1). Terrain points converted into meshes are then modified in polygon modeling software such as Cinema 4D (Egel, Bärtels, & Schneider, 2019), while plants are reconfigured with cloning tools on modified topography using Krakatoa (Thinkbox software, 2018), and reassembled in CloudCompare (Girardeau-Montaut, 2021) as an altered point cloud model (Urech et al., 2020). The selective manipulation of point cloud models allows for detailed topographic and vegetation forms to be reassembled, which can inform scenario development with measured and scientifically analyzed landscape characteristics (Mitasova, Harmon, Weaver, Lyons, & Overton, 2012). Thus, the original laser-scanned model acts as a support for the design process to incorporate contextual affinities. However, the final design choice remains immanent to planners and designers, whose expertise might fall short of addressing the complexity of dynamic systems. This limitation calls for iterative modeling based on the performance of the scenario.

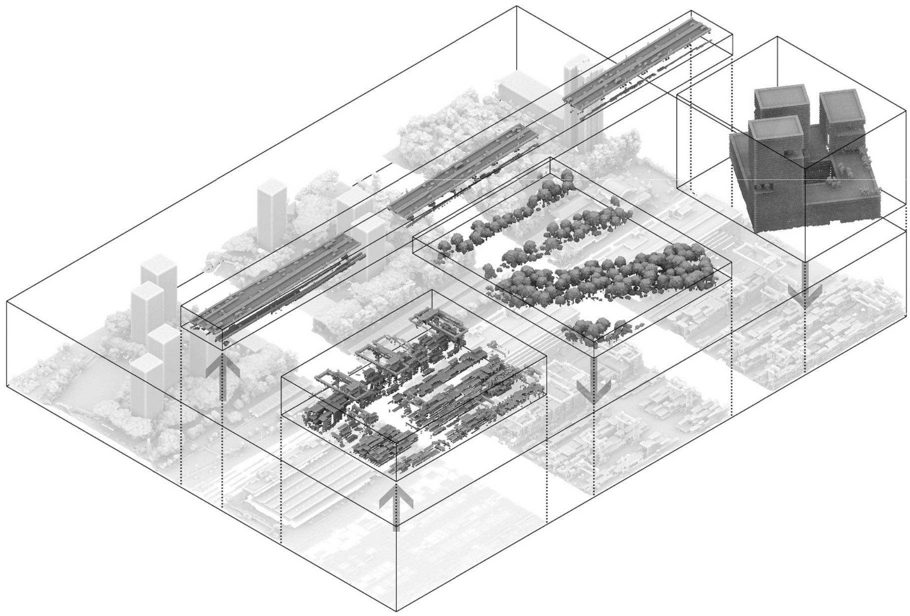


Fig. 1. The laser-scanned model of Tanjong Pagar in Singapore (in light grey) is progressively transformed by point cloud modeling. Obsolete elements, i.e., the viaduct and port structures are selectively removed by segmenting the model. New elements are added by translation, rotation, cloning and normalization to the topographic context. New vegetation is modeled using tree libraries or laser-scanned clusters, while 3D meshes of new buildings are populated with points (Urech et al., 2020).

2.2. Design performance

The concept of performance can be integrated into design development by combining two approaches—that of testing the shape of a design, and iteratively adapting its shape through digital prototyping (Walliss & Rahmann, 2016, 220). Such a process allows for descriptive models designed by landscape architects to be investigated by predictive models of engineers (Girot & Urech, 2016). The first approach involves representing the form of the design with digital modeling. The digital models are then tested with dynamic tools (i.e. CFD simulation). This combination enables simulations to evaluate the performance of designs according to the dynamic conditions of the environment, such as floods (Lin & Girot, 2014) or flow of debris (Hurkxkens, Kowalewski, & Girot, 2020). The second approach uses iteration cycles to develop a prototype. Each cycle enables a new evaluation of the prototype that can be transformed and reevaluated in the next cycle. The evaluation provides feedback by comparing different possible design solutions (Cantrell & Holzman, 2015, 34–50).

2.3. Framework methodology

The proposed design framework consists of four steps linked in a loop (Fig. 2). The design process is steered by iterative point cloud modeling based on the geometric documentation of a site (a). A static (geometry-related) and a dynamic (simulation-related) evaluation are used to examine urban configurations. Parameters are defined based on the geometry of the point cloud model using a static evaluation (b). These parameters are then used for dynamic evaluation simulating flows (c). The evaluations are compared through change detection to provide feedback to the modelers (d), and enable further transformation of the model after the simulation tests.

2.3.1. Geometry

A point cloud model is used as a geometric documentation of the study area (Georgopoulos & Stathopoulou, 2017. The geometry of the model is then manipulated to produce digital prototypes. These altered point cloud models resulting from the manipulation incorporate new scenarios that are evaluated according to their performance, i.e., for thermal comfort in this case study. Generally, evaluations feed an iterative design process useful during project development (Pettit et al., 2019). Here, the design process progresses in loops between iterative point cloud modeling and evaluations of resulting prototypes, thereby gradually synthesizing creative ideas based on site-specific features and dynamic systems. During this process, however, it is difficult to estimate transformations such as displaced terrain volume and the amount of added or removed plants. But since altered models preserve the spatial structure of laser-scanned points, it is possible to measure the transformations, analyze their geometric properties and store them in the models as parameters.

2.3.2. Parameters

A static evaluation of point cloud models highlights morphometric properties (Antonarakis, Richards, & Brasington, 2008; Casas, Riaño, Greenberg, & Ustin, 2012; Sofia, 2020). It also reveals possible flaws in altered models that went unnoticed in the visual assessment during design development. The evaluation generates parameters that are

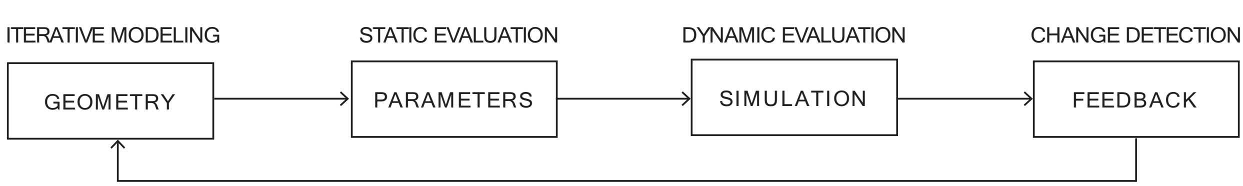


Fig. 2. Overview of the methodological approach linking iterative point cloud modeling (a), static (b) and dynamic (c) evaluations, and change detection (d) in a loop.

attached to each point of the model as scalar values, which are useful for data conversion and comparison. These parameters are either inherent to the geometry—e.g. indexes and coordinates—or computed from the geometry with algorithms for point cloud processing, such as the Point Cloud Library (Rusu & Cousins, 2011) and CloudCompare. The parameters are values of semantic classification (Lohani & Ghosh, 2017), normal direction and cloud-to-cloud distance estimations (Alexa et al., 2003; Girardeau-Montaut, Roux, Marc, & Thibault, 2005) that are used for segmentation by filtering during point cloud modeling. The parameters also include metric values relevant to design development, which can be used to study the height-width ratio of tree crowns and buildings, spatial characteristics of the landscape design (Liu & Nijhuis, 2020), and visual aspects of the urban environment (Portman, Natapov, & Fisher-Gewirtzman, 2015).

2.3.3. Simulation

To address environmental dynamic systems, the evaluation of the site and subsequent design variants involves simulating dynamic conditions (i.e., with CFD). Existing simulation software (e.g., OpenFOAM) is generally unable to handle point cloud models directly. However, the models can be converted into the 3D geometry appropriate for simulation software. In this study, all geometric information is extracted from point cloud models, based on the classification of three main categories: terrain, buildings and vegetation (Fig. 3).

Terrain points are converted and interpolated into a digital terrain model (DTM) using the Raster Map function in CloudCompare with 1 m grid distance. Existing and new buildings are reconstructed as simple block models (level of detail LOD1 according to CityGML) using the footprint extracted from classified point cloud models, and extruded according to the height of the point cloud model (Maragkogiannis, Kolokotsa, Maravelakis, & Konstantaras, 2014). The reconstruction, done in Rhinoceros 3D (McNeel, 2018) with a low level of detail, optimizes computation time for the wind simulation, and facilitates meshing in OpenFOAM (Mughal et al., 2021). The vegetation points are extracted from the point cloud model using the classification, and converted into a 4 m voxel grid with the Distance Map function in CloudCompare, to be used for the CFD simulation (Kiyono, Asawa, & Oshio, 2018). A grid sensitivity analysis determines the appropriate voxel size for the control case as implemented by Mughal et al., 2021, and can be similarly conducted for the design variants. The grid independence study is conducted until the results become independent of the grid size, i.e., until a further improvement in the grid size no longer affects the results.

2.3.4. Feedback

Iterations between design development and evaluation can take place in short sequences of visual feedback, or adopt more elaborated feedback by integrating dynamic evaluation to investigate performance issues. The combination of detailed point cloud models and dynamic simulations improves the accuracy of urban microclimate studies (Kiyono et al., 2018; Maragkogiannis et al., 2014; Mughal et al., 2021; Sun et al., 2021; Xu et al., 2021). However, it is difficult to assess minute changes of wind regime during design development, and identify potential improvement of the urban configuration. In order to differentiate and favor one scenario among others, a numeric change detection is used between pairs of models to compare how the change impacts the performance. The comparison between the simulations highlights significant and small differences, which steers the design development and iterative modeling. The ensuing feedback loop progressively indicates optimizations in the performance of ecosystem services and urban spaces.

3. Implementation

3.1. Case study

The framework introduced in this study was tested and implemented in a realistic setting located in Tanjong Pagar, Singapore (Fig. 4a). The site area of 225 ha (1500 m × 1500 m) is situated at the terminus of a former railway line (Fig. 4b). At present, the area comprises parts of a cargo port with large logistics buildings, the Keppel Viaduct, different typologies of residential buildings and the last mile of the former rail line crossing the island of Singapore. The railway service was discontinued in 2011, and the rails removed subsequently. The Corridor runs along with major topographic features of Singapore, including the hills Bukit Batok and Bukit Timah in the Central Catchment Area and the Kent Ridge in the southern tip of the main island, and borders a range of environments, from dense urban infrastructure to patches of primary forest (Yee, Corlett, Liew, & Tan, 2011). According to the Köppen-Geiger climate classification, Singapore has a tropical rainforest (*Af*) climate with very humid conditions, an average temperature of 27 °C, and a significant amount of rainfall throughout the year (2380 mm/pa) (Fong & Ng, 2012). The prevailing wind direction is north-north easterly during the northeast monsoon and southerly to southeasterly during the southwest monsoon. Stronger winds are observed during the northeast monsoon. The mean annual relative humidity is 83.9%.

3.2. LiDAR data

Data used in this study was acquired with laser-scanning technology, or LiDAR, through an aerial survey in 2014 using an Optech Pegasus HA500 sensor at a planar density of about 30 points/m^2 (Fig. 4b). Supplementary data was collected with a terrestrial survey in 2017 using

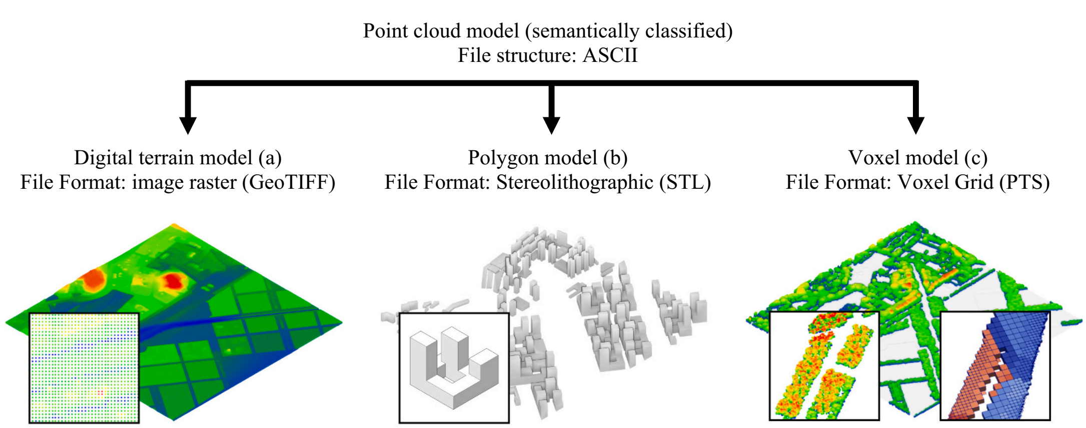


Fig. 3. Point cloud models are converted according to classification (see Section 4.1): topography as digital terrain model (a), buildings as volume polygons (b), and vegetation as voxels that are then reconstructed as volumetric meshes (c). Scalar values stored in point cloud models are exported as Voxel Grids, that is, from LAZ or TXT to PTS file format.

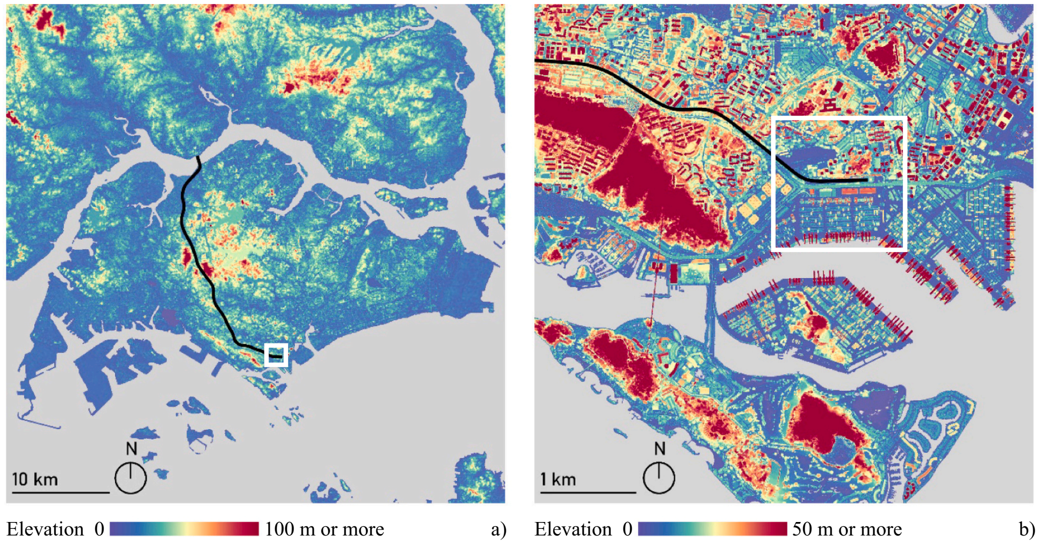


Fig. 4. The elevation maps of the main island (NASA/METI/AIST/Japan Spacesystems and U.S./Japan ASTER Science Team 2019) (a) and of the district Tanjong Pagar (Singapore Land Authority, 2014) (b) show the former railway line crossing Singapore (in black) and the case study area (framed in white).

the Riegl VZ1000. Since the site presents negligible differences between 2014 and 2017, the datasets were combined, reclassified, and subsampled to 20 cm between points to produce a point cloud model representing the current situation. This model acts as the geometric documentation of the site and is taken as a reference for the ensuing design process.

3.3. Simulation data

Numerical analysis combining CFD and radiative heat transfer analysis can predict the thermal environment in urban settings (Tominaga, Sato, & Sadohara, 2015). A modified version of the OpenFOAM is used in the current study developed by Swiss Federal Laboratories for Materials Testing and Research (EMPA) (Kubilay, Derome, & Carmeliet, 2018; Manickathan, Defraeye, Allegrini, Derome, & Carmeliet, 2018). Heat and moisture transport in the air, heat transport in the building materials and wind flow are solved in this fully integrated 3D urban microclimate model.

A radiative exchange between surfaces, including the long- and short-wave radiation, are integrated into the model. Steady state Reynolds-averaged Navier-Stokes (RANS) is solved iteratively with unsteady heat transfer in building materials through a coupled mechanism to model transport in air and building materials. A leaf energy balance is used to determine the heat fluxes, and vegetation is modeled as a porous medium for the flow of moist air. The cooling effect of trees is studied with environmental factors (wind speed, air temperature, relative humidity and solar radiation intensity) and tree properties (leaf size, stomatal resistance and Leaf area density -LAD). The model has been modified for the local conditions in Singapore to include stomatal resistance.

The prevailing wind direction used in simulations is south-north with a magnitude of 2.3 ms^{-1}. The inlet conditions for the model are obtained from Urban Tethys-Chloris (UT&C) (Meili, Manoli, Burlando, Bou-Zeid, et al., 2020). UT&C has been validated in Singapore and has shown good agreement with the local observations in this area. The maximum ambient temperature obtained from the model is 33 °C, while the minimum is around 25 °C. The relative humidity varies between 53% and 86%. Common street trees in Singapore are considered with a leaf area index (LAI) of 2, obtained from the National Parks (NParks) database (National Parks Board, 2019). LAD (1 m^2 m^{-3}) is calculated from LAI with a stomatal resistance of 150 sm^{-1}, leaf size 0.1 m and albedo 0.15. Standard material properties such as density, thermal conductivity, emissivity and albedo for concrete building facades, asphalt (pavement) and soil are considered for simulations.

3.4. Modeling workflow

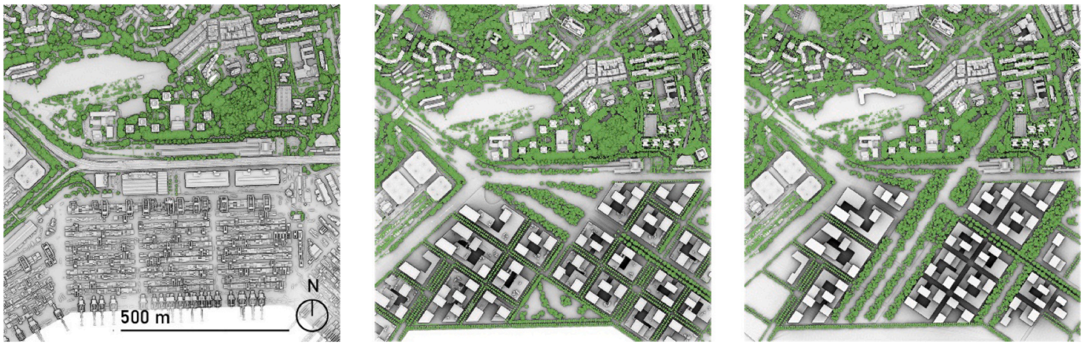
The point cloud model provides all geometric information of the initial urban scene. First, the polygon meshing process was discretized in each design scenario with varying meshing elements (Fig. 3), then a mesh density experiment was carried out for each scenario to reach reliable results (Mughal et al., 2021). This process was used to convert the model and extract the exact building height, footprint and envelope information. The position, shape and height of plants were also collected using the point cloud model and converted according the altered position of urban trees in each design scenario. The wind flow simulation was then performed with OpenFOAM on a duration of 24 h. For each loop of iterative modeling, a simulation was repeated under the same conditions. Finally, the simulation results were visualized on the respective point cloud models by interpolating wind speed values onto adjacent coordinate values using CloudCompare. The interpolation is based on the median value of the ten nearest wind speed values to maintain the precision of the simulation.

4. Results

The proposed framework was applied in a series of scenarios to evaluate and transform a realistic setting located in the district of Tanjong Pagar. Scenario I consists of a geometric survey entirely based on laser-scanned data (Fig. 5a), and was tested for thermal comfort with a CFD simulation. These initial simulation results indicated possible design strategies for thermal comfort in Singapore (Ruefenacht & Acero, 2017). New buildings aligned with the prevailing wind direction are proposed in the port area, which is planned as an extension of the central business district (Urban Redevelopment Authority, 2019). The scenarios for a new urban landscape were discussed between architects and engineers, resulting in two feedback loops which were implemented in scenarios II and III (Fig. 5b and c).

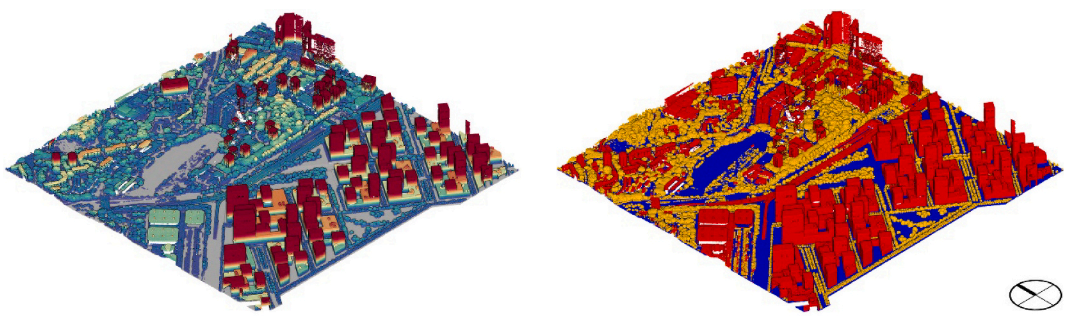
4.1. Iterative design and static evaluations

The point cloud model of every scenario was classified using the algorithms of the GIS software Global Mapper (Blue Marble, 2018) to identify ground points and calculate the height above ground (Fig. 6).



Scenario I (existing) a) Scenario II (design) b) Scenario III (design) c)

Fig. 5. The point cloud model produced with laser-scanning, shown here in plan view, is used as the source model for design development (a). The source model is then transformed into altered point cloud models representing different design scenarios (b, c). Both design scenarios have an equivalent building volume and a canopy cover of 71 ha.

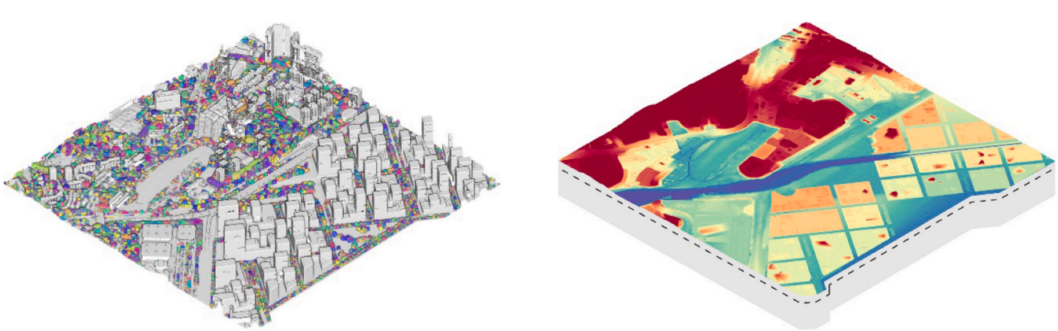


Height above ground 0 60+ m a) b)

Fig. 6. Classification of the altered point cloud model that represents Scenario II (design). The ground, shown in grey, is classified first, allowing then to compute the height above ground of the land cover (a). Semantic information is attached to the altered point cloud model using classifiers (b).

The settings used to classify the ground in Global Mapper were a base bin size of 1 m, a minimum height of 0.5 m, a maximum height delta of 13 m or more, a terrain slope of 15 degrees, and a maximum building width of 200 m. The remaining points that constitute other land covers were then separated into subclasses using two passes of classification in Global Mapper with different settings. A second pass allowed to classify points that were discarded by the first pass, while errors of classification were corrected manually in CloudCompare. The scalar values of object classes can be generated with any classification software for LiDAR data, such as LAStools (Isenburg & Shewchuk, 2019) or LIS Pro (Laserdata, 2019). The low point density on high-rise facades created significant classification errors (particularly on vertical surfaces) and this was solved with multiple passes.

The static evaluation analyses both original and transformed geometry of the altered model, thus providing a comprehensive overview of the transformed site. Objects of the same type were analyzed, for example, based on the inclination of neighboring points to compute the roof area of buildings or to indicate terrain that has more potential of storing rainwater, or based on point distribution to segment the model for inventory (Fig. 7a). Ground points separated through the classification were used to calculate the volume of the terrain (Fig. 7b).



a) b)

Fig. 7. Static evaluation of Scenario II (design). The segmentation with connected components implemented in CloudCompare at Octree Level 12 distinguishes 16,460 vegetation groups, most of which correspond to individual trees (a). The 2.5D volume calculation of the new terrain, computed in CloudCompare, interpolates areas occluded by buildings and counts 13,3 million m^3 above the elevation of 0 m (b). The difference of cut and fills between the original terrain laser-scanned in 2014 and modified terrain is of 753,130 m^3.

4.2. Iterative design and dynamic evaluations

Vegetation plays a beneficial role in regulating the heat for thermal comfort and therefore represents an important ecosystem service in urban environments (Gillner, Vogt, Tharang, Dettmann, & Roloff, 2015; Shashua-Bar, Tsiros, & Hoffman, 2012). To study thermal comfort (affected by air advection) in these scenarios of urban densification, the configuration of urban vegetation and built form was assessed through spatial information and dynamic simulation. Testing the performance of scenarios was important for understanding how the design impacted and contributed to the site.

The iterative design loop focused on evaluating designs based on the impact of urban parks on the local thermal environment through wind modification. The cooling intensity of greenspaces was evaluated and compared in each case. Three iterations were performed; the first iteration (I) involved producing a source model from the survey data (Fig. 8a). This enabled the simulation to be validated on the existing site with the local climate. The second iteration (II) consisted of using point cloud modeling to produce a new design scenario (altered model) for subsequent evaluations (Fig. 8b).

The first two evaluations (I and II) provided an analysis on how the design would influence the current situation. The evaluation included the calculation of wind flow field (Salim, Mohamed, & Grawe, 2015). This analysis has shown a decrease in wind speed around the historical train station (about −1.5 m/s) and near the existing housing blocks (about −1 m/s). These observations visually informed the decisions on how to adapt the model for a third iteration (III) (Fig. 8c). The altered model (Scenario II) was subsequently adapted by rearranging trees in the main park to form breezeways parallel to the prevailing wind direction. Also, the space between buildings was increased in some areas to allow greater wind flow, and reduced in other areas to provide more shade. The area of the canopy and the volume of the building remained constant in both design scenarios (II and III).

The iterations between point cloud modeling and simulation enabled the feedback loop based on the geometry of the point cloud models. The CFD simulation was set up to determine the wind speed for the three scenarios. The simulation was initialized with a wind field acting in the predominant wind direction, from south to north. For each iteration, the point cloud model of the existing site was converted to volumetric geometry through a polygon meshing process as detailed in Fig. 3. In order to offset the inconsistencies in the results, the experiment was repeated for mesh density around building region until the forces do not change and further increasing mesh density will not change the accuracy of the simulation.

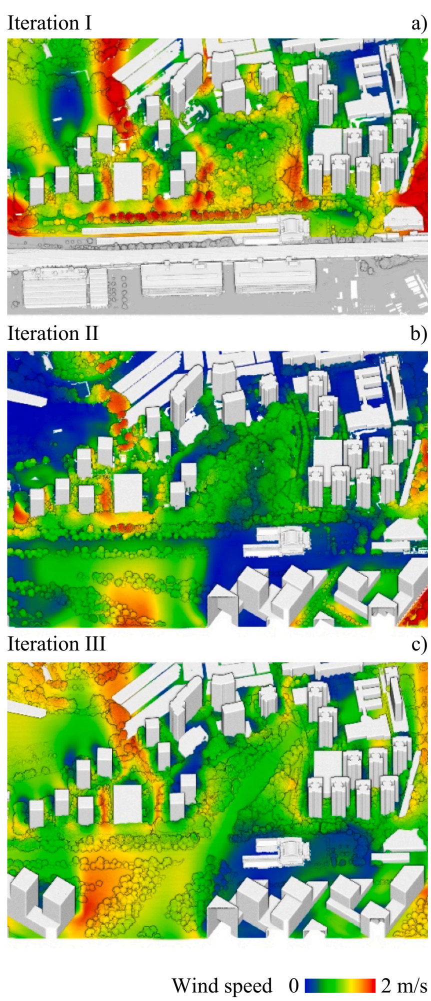


Fig. 8. The CFD simulation of wind currents matches the predominant wind direction in Tanjong Pagar. The buildings are included in the simulation, although shown here in white to clarify the illustration. For computational optimization of Iteration I, the Keppel Viaduct and Port are excluded from the CFD simulation (shown in grey), being scheduled for complete removal.

4.3. Numeric change detection on point cloud models

The change of wind speed at street level was investigated by interpolating the simulation values of both Iterations II and III onto the same model in CloudCompare. There, the wind speed values resulting from Iteration II were subtracted from the values of Iteration III, giving a precise indication on how and where the wind flow has changed (Fig. 9).

By freeing a block-wide opening in the new built area (circle 1 in Fig. 9), the wind flow became more distributed in the second design scenario, decreasing the wind speed at the previously narrow passage,

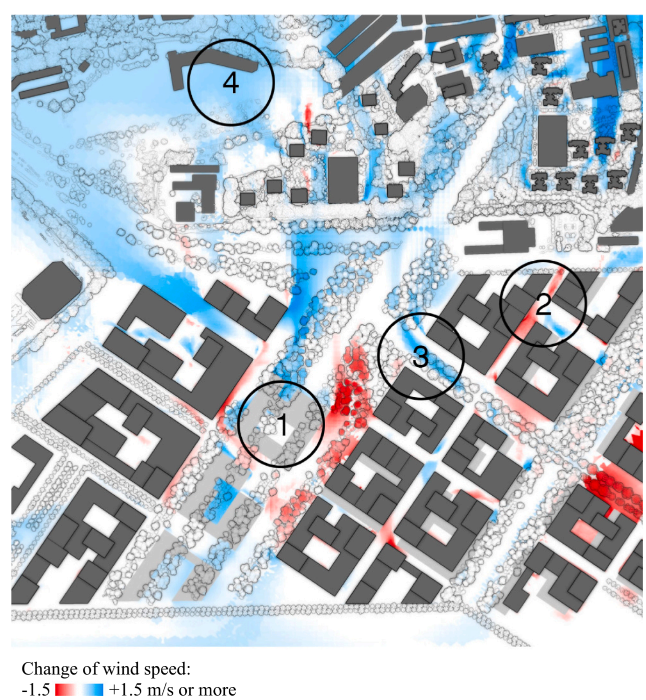


Fig. 9. The change of wind speed is visualized on the 3D point cloud model by comparing the values resulting from the simulation of iteration II and III. The change of configuration of the urban landscape results in an increase (in blue), a decrease (in red), or an invariance (in white) of the wind speed. Shifted building volumes are excluded from the comparison (colored in grey). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

but increasing the speed behind the tower that was projecting a wind shadow. The narrowing of some streets created wind blockage triggering a decrease of wind speed by 1,5 m/s (circle 2 in Fig. 9), while the ensuing widening of the main spaces in the main wind direction triggered an increase in perpendicular streets (circle 3 in Fig. 9).

Although the vegetation area and building volume remained constant between the two design scenarios, the configuration of iteration III enabled more continuous airflow and thus a more effective dissipation of urban heat. In consequence, the iterative design process implemented here demonstrates that different dragged features can alter the wind regime completely, as seen in the top left corner of the image which shows a general increase in wind speed (circle 4 in Fig. 9). Eventually, this might result in an improved thermal sensation across the entire area due to forced advection (Bartesaghi-Koc et al., 2021). Other factors in addition to wind speed also play a part in improving thermal sensation namely shading, mean radiant temperature, evapotranspiration by trees, time of the day etc. Further analysis involving thermal comfort indices such as Universal Thermal Comfort Index (UTCI) or Physiological Equivalent Temperature (PET) can additionally support the comparison of the scenarios in terms of thermal comfort.

5. Discussion and conclusions

Landscape architects, planners and designers are required to justify proposals not only from an aesthetic or visual point of view, but also in terms of the contribution they make to the overall performance of environments. Under this holistic approach, urban and natural landscapes are the result of complex, dynamic and evolving phenomena that vary in space and time; hence this should be examined and visualized as dynamic factors in constant process of adaptation and self-organization (Cadenasso et al., 2013).

Including traits of the landscape and forecasting the impact of change or adaptation has therefore become a primary requisite for developing planning and design scenarios (Pettit et al. ., 2019; Srivastava, Scott, & Rosier, 2021). This attitude can be traced back to the principles of biologist and pioneering town planner Patrick Geddes, who conducted comprehensive surveys to support planning tasks (Goist, 1974, 33). His approach of including surveys in the planning process underpinned the ecological method, which was theorized by Ian McHarg – and later applied by Michael Hough (1994) –, who pioneered the integration of the 'systems-thinking' approach into landscape architecture and planning (McHarg, 1969, 35; Hough, 1995). With frameworks such as Geographic Information Systems (GIS) and Geodesign (Afrooz, Ballal, & Pettit, 2018; Srivastava et al., 2021; Steinitz, 2012), these ecological methods currently provide normative tools, network-based collaborative governance techniques and decision support for designers and planners (Pettit et al. ., 2019). In this view, the design develops primarily as a consequence of analysis rather than a creative intention. This creative capability is necessary to approach the landscape not as a problem to be solved, but rather as a system to be incrementally developed (Davies & Shakespeare, 1993).

The novel methodological framework presented, tested and discussed here is the first attempt to incorporate a holistic approach into landscape planning and design by integrating detailed digital modeling and iterative performance assessments using emerging data-driven technologies and methods capable of dealing with complex-dynamic problems (i.e. urban overheating, flooding, droughts, etc.). This framework has been successfully applied in a case study in Tanjong Pagar, Singapore, with particular focus on thermal comfort, and it is anticipated that this can be equally implemented by geospatial scientists, researchers and design practitioners if equivalent data and software are available. The availability of open LiDAR data is increasing, while portable-device technologies are becoming more affordable and accessible to users (i.e. smartphones, handheld laser scanners). If equivalent data is not available, point cloud models can be equally derived from photogrammetry-based models collected by unmanned aerial vehicles (UAVs) at relatively lower costs. It is also expected that this method can bring together human-informed ideas for the creation of different landscape and planning scenarios (or iterations) to negotiate design solutions based on defensible scientific evidence (i.e. results from simulations).

5.1. Evidence from physical forms

Although the iterative design method presented in this paper aligns with the principles of survey and analysis, it contrasts with the determinism of the ecological method by combining analytical and creative design approaches (Turner, 1996, 141–53). This method does not point towards a particular design hypothesis, nor does it influence the transformation towards a particular design outcome. The transformation of a source point cloud model provides evidence about the existing landscape form. The creativity of designers results from interpreting the site with the source model, rather than being prescribed by an analytical outcome. The measured evidence provided by the source model establishes a close relation with the design and interrelates a variety of considerations. The parameters retrieved from laser-scanned data on topographic and vegetation structures influence how spatial configurations are imagined and developed during design.

5.2. Evidence from simulation

The evaluation of point cloud models provides a base of information to advance the design iteratively. The iterations harness the existing situation as a stepping-stone for improvement. But while the source model provides evidence about existing conditions, the evaluation phase provides evidence on how the design might perform in the future. At the beginning of the design process, design intentions may be faulty or incompatible with site conditions, but with the evidence obtained from point cloud-based simulation results, decisions can be taken to progress towards a final proposal. The evidence from simulations informed on how to improve the performance of current and transformed situations, and develop cooling spaces in the hot urban environment of Singapore.

5.3. Calibrating a design for the site

The iterative process with evidence from both form and simulation contributes to shaping the landscape through both empirical observations and creative intentions. The iterations enhanced the reciprocal influence between the existing site and prospective design ideas. This calibration between the existing and envisioned landscape is pursued with computer-based 3D modeling to establish a dynamic exchange between parameters and design decisions (Walliss & Rahmann, 2016). Computational design is based on iterative approaches that allow the site to be addressed within a more complex and adaptable workflow with local variables (Cantrell & Mekies, 2018, 28–33). With the method proposed in this paper, the point cloud model provides the parameters while the simulations progressively adapt the design decisions. The reciprocal influence between existing and envisioned landscape leads to treating the built environment as a perpetually evolving construct that could accumulate locally in more permanent and characteristic forms.

5.4. Final remarks

The research presented in this paper aims at extending the use of digital models in urban landscape design. The combination of iterative point cloud modeling and simulation introduced here is a step forward in shaping the physical environment both creatively and scientifically. The concluding remarks summarize potential improvements of (1) the workflow, (2) the computation, and (3) the application described in this study.

1) The proposed framework uses point cloud modeling to include site-specific qualities for aesthetic development, and to perform precise simulations of the physical environment via CFD software, different to existing approaches using geometric reconstructions and parameterizations. The entire 3D modeling process occurs within point cloud models; the data conversion only applies to the simulation step and is due to a limitation of the digital formats supported by the simulation software. A workflow improvement would require the support of point cloud models without a need for geometry conversion.
2) Extensive geometric simplification was necessary to reduce computing time, and involved flattening the topography, normalizing the vegetation, and discretizing the building geometry. Such a geometric simplification is questionable, considering that the analysis of thermal comfort occurs at human height, which is easily exceeded by topographic variations influencing near-ground airflow. In this study, the computing time for a 24 h simulation was 156 h, in a parallel run using 36 processors on a single processing node. The computation time could be optimized from hours to minutes, either by changing inflow boundary conditions tested by a surrogate model, by approximating simulations using deep learning (Kochkov et al., 2021; Sanchez-Gonzalez et al., 2020), or by implementing quantum computing in fluid dynamics (Bharadwaj & Sreenivasan, 2020; Lu, Hu, Xie, & Zhang, 2021).
3) The change detection analysis enables the comparison of multiple scenarios and derives observations for optimizing the spatial configuration according to the existing site. Therefore, the iterative workflow should be fast in alternating between design development and feedback. In this study, however, the iterative workflow in Tanjong Pagar required a long process for set-up, data conversion and simulation of every design scenario. This time lag resulted in developing design scenarios with broad differences instead of refining the scenarios iteratively, as the analysis-modeling-simulation-feedback workflow would allow.

Urban environments encompass many dynamic factors that require appropriate simulation models. An improved integration between physical form and performance is needed to address these dynamic systems at play on large-scale landscapes. Supporting the design process with iterative point cloud modeling offers a significant advantage for synthesizing adaptive solutions, for transcalar design, and for creative and aesthetic integration.

Author contribution

Philipp Urech performed design development, modeling, writing – original draft and conceptualization. Muhammad Omer Mughal performed simulation and writing – technical description. Carlos Bartesaghi-Koc performed writing – review, editing and conceptualization.

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Declaration of competing interest

The authors declare no conflicts of interest.

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